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Revisiting yield gaps and the scope for sustainable intensification for irrigated lowland rice in Southeast Asia

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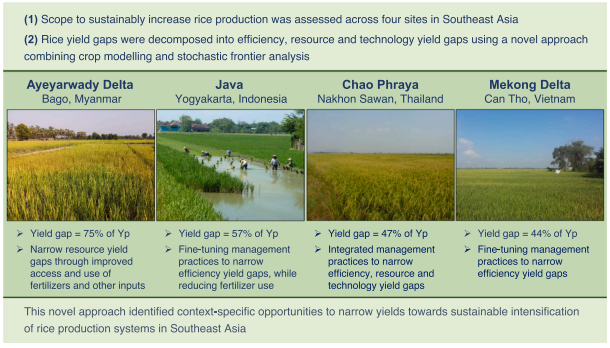
HIGHLIGHTS

- Analysis rice yield gaps is needed to better understand how to sustainably increase rice production across Southeast Asia.
- Rice yield gaps (Yg) for four countries in Southeast Asia were decomposed into efficiency, resource, and technology Ygs.
- Ygs were mainly attributed to resource and technology Yg in Myanmar, and to efficiency and technology Yg in Indonesia.
- Yg closure requires increased N in Myanmar, reduced N in Indonesia, and fine-tuning N management in Thailand and Vietnam.
- This novel approach identified opportunities for sustainable intensification of rice production in Southeast Asia.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: Recent studies on yield gap analysis for rice in Southeast Asia revealed different levels of intensification across the main 'rice bowls' in the region. Identifying the key crop management and biophysical drivers of rice yield gaps across different 'rice bowls' provides opportunities for comparative analyses, which are crucial to better understand the scope to narrow yield gaps and increase resource-use efficiencies across the region.

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OBJECTIVE: The objective of this study was to decompose rice yield gaps into their efficiency, resource, and technology components and to map the scope to sustainably increase rice production across four lowland irrigated rice areas in Southeast Asia through improved crop management.
METHODS: A novel framework for yield gap decomposition accounting for the main genotype, management, and environmental factors explaining crop yield in intensive rice irrigated systems was developed. A combination of crop simulation modelling at field-level and stochastic frontier analysis was applied to household survey data to identify the drivers of yield variability and to disentangle efficiency, resource, and technology yield gaps, including decomposing the latter into its sowing date and genotype components.
RESULTS AND CONCLUSION: The yield gap was greatest in Bago, Myanmar (75% of Yp), intermediate in Yogyakarta, Indonesia (57% of Yp) and in Nakhon Sawan, Thailand (47% of Yp), and lowest in Can Tho, Vietnam (44% of Yp). The yield gap in Myanmar was largely attributed to the resource yield gap, reflecting a large scope to sustainably intensify rice production through increases in fertilizer use and proper weed control (i.e., *more output with more inputs*). In Vietnam, the yield gap was mostly attributed to the technology yield gap and to resource and efficiency yield gaps in the dry season and wet season, respectively. Yet, sustainability aspects associated with inefficient use of fertilizer and low profitability from high input levels should also be considered alongside precision agriculture technologies for site-specific management (i.e., *more output with the same or less inputs*). The same is true in Thailand, where the yield gap was equally explained by the technology, resource, and efficiency yield gaps. The yield gap in Indonesia was mostly attributed to efficiency and technology yield gaps and yield response curves to N based on farmer field data in this site suggest it is possible to reduce its use while increasing rice yield (i.e., *more output with less inputs*).
SIGNIFICANCE: This study provides a novel approach to decomposing rice yield gaps in Southeast Asia's main rice producing areas. By breaking down the yield gap into different components, context-specific opportunities to narrow yield gaps were identified to target sustainable intensification of rice production in the region.

1. Introduction

Rice (*Oryza sativa* L.) is the main staple food for more than half of the world's population, many of whom live in developing countries (Pandey et al., 2010). Meeting the global rice demand in the future must be achieved through sustainable increases in rice production in the main rice growing areas of Southeast Asia to avoid further conversion of land to agriculture and to reduce the environmental and health impacts of intensive production (Godfray et al., 2010; McKenzie and Williams, 2015). Other grand challenges facing agricultural systems worldwide include the adverse effects of climate change, urban and industrial encroachment, biodiversity loss and associated loss of ecosystem services and soil degradation (Silva and Giller, 2021; Bouman et al., 2007; Rosegrant and Cai, 2002). Against this background, sustainable intensification was proposed as a strategy to increase crop productivity, through yield gap closure on existing agricultural land, while improving resource-use efficiencies and reducing environmental externalities (Cassman and Grassini, 2020; Tilman et al., 2011).

Assessing the potential for sustainable intensification is particularly important in many Asian countries where rice is the staple food and irrigated lowland rice occupies a large proportion of the total agricultural land (GRiSP, 2013). Indonesia, Vietnam, Thailand, and Myanmar are responsible for nearly 85% of the annual rice production in Southeast Asia (FAOSTAT, n.d.). Indonesia is the 3rd world's largest rice producer and has been able to achieve near self-sufficiency in recent years (Agus et al., 2019). However, some of the country's most productive agricultural areas, such as in Java, are being lost as land is converted to residential, commercial, or other purposes (Rumanti et al., 2018). Vietnam has become one of the world's largest rice exporters, and the Mekong delta produces nearly 60% of Vietnam's total rice output (Tong, 2017). However, the rapid intensification of rice production in Southern Vietnam from the late 1990s resulted in an overreliance on agrochemicals that are becoming increasingly expensive (Stuart et al., 2018a), which makes it important to consider improvements in resource-use efficiency and profitability in addition to increases in rice yield. The same is true in Thailand, one of the world's largest rice producers and exporters. About half of the total annual rice produced in Thailand comes from the Chao Phraya river basin (Stuart et al., 2018b), where rising rural wages and input costs have magnified the focus on increasing the profitability of rice production. Lastly, Myanmar is the fourth largest rice producer in Southeast Asia, with over 55% of the rice area located in the Ayeyarwady delta (Thwe et al., 2019). Here, rice productivity is significantly lower than in neighboring countries mostly due to low input use, limited training, and poor infrastructure. However, the government recently set targets to double agricultural productivity and farmers' incomes in a little over 10 years (Dubois et al., 2019).

Strategies to increase food production and meet the future food demand must reconcile environmental and socio-economic factors with narrowing (or maintaining) the existing yield gap between the potential yield (Yp) for irrigated crops and the actual yield (Ya) observed in farmers' fields (van Ittersum et al., 2013). Yield gap analysis plays a key role in sustainable intensification research as it identifies the contribution of biophysical and management factors, and their interactions, to actual yields (van Ittersum and Rabbinge, 1997; Evans and Fischer, 1999; van Ittersum et al., 2013). Yet, to increase crop yields sustainably, it is also important to understand the broader socio-economic context in which farmers operate to prioritize the 'sustainability' and 'intensification' pathways most suitable for a given farming system (Laborte et al., 2012; Stuart et al., 2016; Struik and Kuyper, 2017; Silva et al., 2021). Comparative studies, building upon common frameworks and methods, of farming systems in different stages of intensification or affected by different structural transformation of national economies are particularly useful in this regard.

Recent studies on yield gap analysis for rice in Southeast Asia revealed different levels of intensification across the main 'rice bowls' in the region (e.g., Laborte et al., 2012; Stuart et al., 2016; Silva et al., 2017a, 2017b; Radanielson et al., 2019). Such diversity provides opportunities for identifying the key biophysical and management drivers of rice yield gaps in a comparative way and, hence, to explore opportunities to narrow yield gaps and increase resource-use efficiencies. This study revisits the analysis of Stuart et al. (2016) and expands it with a field-specific yield gap decomposition for two growing seasons, representing one annual cropping cycle, across four main irrigated lowland rice areas in Southeast Asia. By doing so, best-bet crop management practices and pathways for sustainable intensification attuned to local conditions can be identified and used to inform policy. The objective of the present study was two-fold: 1) to decompose rice yield gaps while identifying the key biophysical and management constraints to rice yield, and 2) to explore pathways for sustainable intensification across four irrigated lowland rice areas in Southeast Asia in a comparative way. To do so, crop growth modelling was applied to simulate Yp under different management scenarios and stochastic frontier analysis was

used to decompose yield gaps across a sample of rice fields in each of the irrigated lowland sites studied.

2. Concepts and definitions

Yield potential (Yp) is defined as the yield of a crop cultivar in a given cropping season when grown with water and nutrients non-limiting and biotic stresses effectively controlled (Evans, 1993; van Ittersum and Rabbinge, 1997). Three variants of Yp are defined in this study to consider the impact of the main factors controlled by farmers driving Yp variability namely sowing dates and variety characteristics (Fig. 1).

Yp_a refers to the potential yield simulated with a crop growth model for the highest yielding variety and for the optimum sowing date of the cropping season within a given site. Yp_a is thus an indicator of the potential yield of a given site for a given season using the optimum sowing date and the highest yielding variety available to farmers. The optimum sowing date of the growing season was defined as the date with the highest Yp within a three-month sowing window around the mean sowing date observed in farmer's field data for a particular season (i.e., mean sowing date ± 6 weeks).

Yp_b refers to the potential yield simulated with a crop growth model for the highest yielding variety and for the field-specific sowing dates observed in a given site. The highest yielding variety used as a benchmark for Yp_a and Yp_b was the variety with the highest average Yp, among the varieties used by farmers, in a given growing season. Yp_b informs about the potential yield for the sowing date reported in an individual field and considering the highest yielding variety available. Yp_a and Yp_b are then indicators of yield potential for the highest yielding variety available at each site when it is grown in the optimum sowing date and in the farmer reported sowing date, respectively.

Yp_c refers to the potential yield simulated with a crop growth model considering both varieties and sowing dates as observed in farmers' fields. Thus, Yp_c refers to the actual variety used by the farmer on its actual sowing date. As defined here, the difference between Yp_b and Yp_c does not consider genotype x sowing date interactions, which are known to influence resource use efficiencies at crop (Evans and Fischer, 1999) and cropping systems levels (Guilpart et al., 2017). Yp_b and Yp_c consider observed sowing dates and the results must be interpreted accordingly, as explained by the variety used.

Two additional yield levels are defined to capture crop productivity under actual farm conditions (Fig. 1). First, the technical efficient yield (Y_{TEx}) refers to the highest possible yield obtained given observed levels of inputs in a well-defined biophysical environment (Silva et al., 2017a, 2017b). Y_{TEx} can be estimated with methods of frontier analysis (Farrell, 1957) applied to individual farmer field data containing detailed information on crop yield, input use, management practices, and biophysical conditions. Second, the actual yield (Ya) refers to the yield observed in farmers' fields as requested in e.g., farm surveys.

Four major yield gaps can be estimated based on the five yield levels previously introduced (Fig. 1). The total yield gap refers to the difference between Yp_a and Ya, which can also be expressed by the ratio between Ya and Yp_a defined as yield gap closure. The total yield gap can be further decomposed into technology, resource, and efficiency yield gaps (see Silva et al., 2017a, 2017b) for a visual illustration of these concepts).

The technology yield gap is quantified here as the difference between Yp_a and Yp_c, which indicates the yield gap due to sub-optimal sowing date and variety choice from a production perspective. The use of Yp_c in the calculation of the technology yield gap, instead of the highest farmers' yields (Y_{HF}, i.e., the average Ya for the fields above the 90th percentile of Ya) as in Silva et al. (2017a, 2017b), implies that the technology yield gap estimated here is only explained by sowing practices and crop varieties differing between Yp_a and Yp_c. When the technology yield gap is defined as the difference between Yp_a and Y_{HF}, as in Silva et al. (2017a, 2017b), then its magnitude can be attributed to resource yield gaps of specific inputs (i.e., partial shifts of the production frontier) or to the adoption of precision agriculture practices, new varieties, or manipulation of sowing practices (i.e., total shifts of the production frontier; Silva et al., 2017a, 2017b). Conversely, when the technology yield gap is defined as the difference between Yp_a and Yp_c, as done in this study, then it can only be attributed to the latter factors. In this way, the technology yield gap can be further disaggregated into a 'sowing date yield gap' (the difference between Yp_a and Yp_b) and a 'genetic yield gap' (the difference between Yp_b and Yp_c; Fig. 1). The sowing date yield gap is explained by sub-optimal sowing dates and hence, considers yield response to environmental conditions during the growing season (Jing et al., 2008; Rattalino Edreira et al., 2017; Radanielson et al., 2019). The genetic yield gap is attributed to lower performing varieties from a production perspective as also introduced by Senapati and Semenov (2020).

The resource yield gap is quantified here as the difference between Yp_c and Y_{TEx}, hence it indicates the yield gap associated with insufficient amounts of inputs applied in farmers' fields, which limits the capacity to achieve Yp_c. The use of Yp_c to estimate the resource yield gap is comparable to the concept of 'feasible yield' (Yf; van Dijk et al., 2017) and to

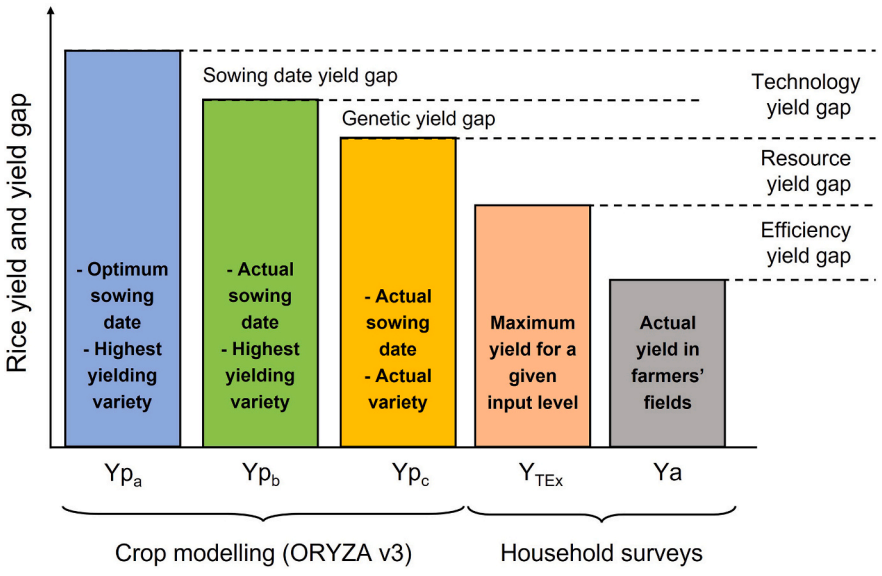

Fig. 1. Concepts and definitions of the yield levels and yield gaps used in this study for decomposing rice yield gaps across irrigated lowland areas in Southeast Asia. Abbreviations: Yp_a, simulated potential yield for optimum sowing date and the highest yielding variety; Yp_b, simulated potential yield for farmers' sowing dates and highest yielding variety; Yp_c, simulated potential yield for farmers' sowing dates and variety used; Y_{TEx}, technical efficient yield estimated with stochastic frontier analysis; Ya, actual yield observed in farmers' fields. Please refer to Section 2 for further information about these yield levels.

the concept of 'highest-farmers' yield' (Y_{HF}) in high-yielding cropping systems (Silva et al., 2017a, 2017b). Yet, Yp_c assumes optimal resource-use efficiencies from an agronomic perspective, whereas Yf and Y_{HF} consider the maximum resource-use efficiencies realized in farmers' fields.

Finally, the efficiency yield gap is quantified as the difference between Y_{TEx} and Ya and hence captures the contribution of different techniques in the use of the technology and resources to actual yields, translating into sub-optimal time, space, and form of the inputs applied. Crop management in relation to a) 'time' refers to the timing of application of the different inputs used by farmers, b) 'space' refers to the spatial variability of input requirement and application, the variability in soil types and their effects on input use efficiency and, c) 'form' refers to the type of inputs used by farmers.

3. Materials and methods

3.1. Study area and household surveys

The study area includes four sites in irrigated lowland rice areas of Southeast Asia (Fig. 2), namely Bago (Ayeyarwady delta, Myanmar), Can Tho (Mekong delta, Vietnam), Nakhon Sawan (Chao Phraya river basin, Central Thailand) and Yogyakarta (Java, Indonesia). In each site, four different administrative units (village or commune) were purposely selected as possible intervention sites for the Closing Rice Yield Gaps in Asia with Reduced Environmental Footprint (CORIGAP) project. Each of the sites represents irrigated lowland rice production, with at least two rice crops grown each year. Within each country, villages were selected based on similar farm size and demographic characteristics and were located within a 25 km radius of each other. In Bago, Can Tho and Yogyakarta, survey respondents were randomly selected from a list of rice farmers from each administrative unit, whereas in Nakhon Sawan, interviews were conducted with all the farmers from a community rice center within each administrative unit. The farm surveys were conducted between 2012 and 2015, depending on the site. Farmers were interviewed using a standard structured questionnaire across all sites requesting information for the largest rice parcel in each farm on inputs used, crop management practices, actual rice production, and field area for the previous two cropping seasons, as well as a set of farm and household characteristics. A total of 100, 180, 180 and 84 farms were interviewed in Bago (2012), Can Tho (2015), Yogyakarta (2014), and Nakhon Sawan (2013), respectively. A subset of the data from the same survey were reported by Stuart et al. (2016; for the wet season only) and Devkota et al. (2019). Additional data on the socio-economic characteristics, rice variety duration, sowing window, and herbicide use are included in this study.

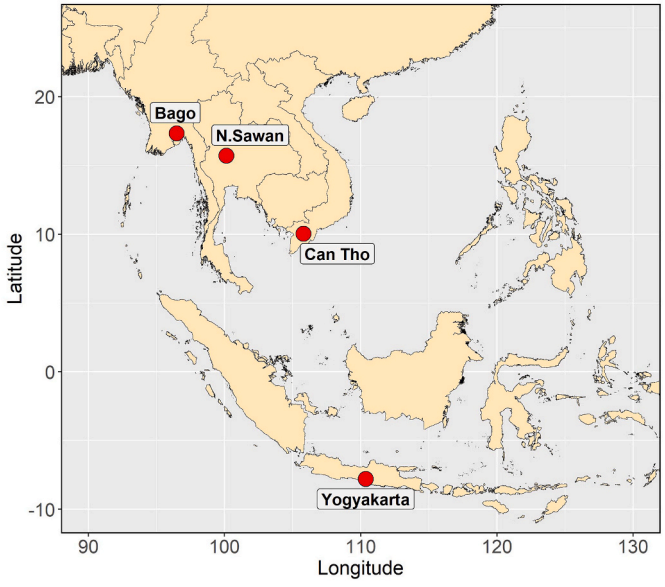

Fig. 2. Location of the irrigated lowland rice areas analyzed in this study: Bago in Myanmar, Nakhon Sawan in Thailand, Can Tho in Vietnam, and Yogyakarta in Indonesia.

The actual yield (adjusted to 14% moisture content) was calculated as the ratio between actual rice production and field area. Individual cases where Ya was greater than Yp_c plus 0.5 t ha^{-1} were removed from the analysis (i.e., Myanmar, $n = 0$; Vietnam, $n = 5$; Thailand, $n = 1$; Indonesia, $n = 21$, where n stands for the number of observations excluded from the analysis in each site). Possible reasons for these extreme values are: 1) misidentification of the rice variety sown, 2) underestimation of field size, and/or 3) overestimation of actual rice production. Descriptive statistics of selected agronomic and socioeconomic factors in each site are presented in Table 1.

Bago, Myanmar, has two major growing seasons per year: the summer season or dry season (DS) from November to May and the monsoon season or wet season (WS) from June to January. In Can Tho, Vietnam, double rice cropping is also dominant, with a winter-spring or DS crop from November to March and a summer-autumn or WS crop from April to July. Farmers in Nakhon Sawan, Thailand, typically grow two rice crops per year: a DS crop from January to May and a WS crop from June to October. In Yogyakarta, Indonesia, rice is grown up to three times a year in some areas: a WS crop from November to March, an early DS crop from April to July, and a late DS crop from July to October. Farmers that do not have sufficient water to grow a second DS crop, typically grow a non-rice dryland crop (i.e., "*palawija*", such as maize, mung bean, or groundnut).

3.2. Crop model simulations to estimate the potential yield (Yp)

The crop model ORYZA v3 (Li et al., 2017) was used to simulate the three variants of Yp considered in this study (Fig. 1). These Yp variants were simulated for each surveyed field in each site where the farm surveys were conducted. The ORYZA v3 model, and its earlier versions, has been extensively calibrated and evaluated to simulate Yp for rice in the main irrigated rice areas of Southeast Asia (Jing et al., 2008; Laborte et al., 2012; Li et al., 2016; Stuart et al., 2016; Radanielson et al., 2019). The model represents rice crop development and growth in response to genotypic, environmental and management factors, and their interactions, considering mechanistic and empirical relationships that are described in Bouman et al. (2001) and Li et al. (2017).

The factors considered in the simulation of Yp included daily weather data for each site where the farm surveys were conducted (Table 1) as well as field-specific farmers' reported rice varieties, crop establishment method and sowing dates (Table 2). For each farmers' field surveyed, daily weather data were obtained from the NASA POWER database (http://power.larc.nasa.gov). These data included daily minimum and maximum temperatures, solar radiation, and rainfall (Suppl. Fig. 1). The varieties simulated in each site were IR50 (Shwe Thwe Yin), IR138 (Mestizo) and IR154 (NSIC Rc222) in Myanmar, Jasmine 85 and OM5451 in Vietnam, RD31 in Thailand, and Ciherang, IR64 and Inpari 6 in Indonesia (Table 2). The main differences between these calibrated varieties in ORYZA v3 are the thermal times controlling crop development and some of the parameters controlling leaf growth and biomass production. Further details about the calibration of the different varieties in ORYZA v3 are reported elsewhere (Boling et al., 2004; Boling et al., 2010; Stuart et al., 2016; Radanielson et al., 2018; Radanielson et al., 2019) and the calibrated crop files for each variety can be found at https://github.com/andomariot/inputs_cropfile_oryza/find/main. If the variety reported by the farmer was not identified among the previously mentioned varieties, then the variety used in the crop model simulations was the most reported variety among the farmers surveyed in Vietnam, Thailand, and Indonesia, respectively. This allows maintaining consistency in Yp_c and reducing uncertainties in Yp

Table 1
Descriptive statistics of selected agronomic and socioeconomic factors for dry season (DS) and wet season (WS) rice across four irrigated lowland areas in Southeast Asia. Average values are shown for each variable with standard deviations between brackets.

	Myanmar		Vietnam		Thailand		Indonesia	
	DS	WS	DS	WS	DS	WS	DS	WS
Actual yield (t ha^{-1})	2.67	2.54	7.86	4.94	4.61	4.75	4.95	4.84
	(0.86)	(0.83)	(0.96)	(0.84)	(1.14)	(0.98)	(2.17)	(1.94)
Input use and management								
N applied (kg N ha^{-1})	30.27	17.53	102.48	92.89	83.86	82.04	197.03	211.77
	(20.09)	(18.72)	(29.53)	(31.90)	(28.96)	(36.42)	(103.03)	(117.33)
P applied (kg P ha^{-1})	1.03	0.37	27.70	25.97	16.68	16.67	18.71	20.21
	(2.55)	(1.40)	(10.32)	(10.97)	(8.82)	(9.33)	(11.89)	(13.68)
K applied (kg K ha^{-1})	0.14	0.00	42.80	39.23	9.55	9.39	36.25	38.44
	(0.62)	(0.01)	(20.11)	(19.40)	(15.96)	(14.87)	(23.81)	(24.96)
Fertilizer splits (#)	1.61	0.89	3.69	3.62	2.79	2.65	2.38	2.44
	(0.87)	(0.83)	(0.82)	(0.86)	(0.41)	(0.48)	(0.76)	(0.68)
Herbicide use (=1 if yes)	0.51	0.00	0.94	0.96	0.53	0.96	0.04	0.02
	(0.50)	(0.00)	(0.24)	(0.19)	(0.50)	(0.19)	(0.20)	(0.13)
Sowing week[1]	12.13	7.44	1.11	2.91	7.33	5.17	8.03	2.75
	(17.19)	(3.62)	(0.94)	(1.70)	(14.42)	(1.67)	(2.92)	(2.13)
Duration of rice varieties[2]								
Short duration (=1 if yes)	0.04	0.00	0.11	0.63	0.00	0.00	0.21	0.18
	(0.20)	(0.00)	(0.32)	(0.48)	(0.00)	(0.00)	(0.41)	(0.38)
Medium-short duration (=1 if yes)	0.39	0.12	0.89	0.37	0.82	0.92	0.76	0.80
	(0.49)	(0.32)	(0.32)	(0.48)	(0.39)	(0.28)	(0.43)	(0.40)
Medium-long duration (=1 if yes)	0.46	0.49	0.00	0.00	0.00	0.00	0.00	0.00
	(0.50)	(0.50)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Long duration (=1 if yes)	0.14	0.38	0.00	0.00	0.18	0.08	0.00	0.00
	(0.35)	(0.49)	(0.00)	(0.00)	(0.39)	(0.28)	(0.00)	(0.00)
Socioeconomic characteristics								
Farm experience (year)	25.07	25.56	25.25	25.33	23.29	25.70	23.42	22.84
	(11.95)	(11.91)	(10.00)	(10.04)	(13.94)	(14.16)	(15.95)	(15.01)
Ratio of rice income (%)[3]	53.92	40.93	46.63	9.44	37.11	32.67	49.59	24.47
	(36.46)	(35.18)	(28.34)	(11.17)	(19.54)	(24.17)	(20.26)	(20.59)
Farm size (ha)	3.03	4.87	2.16	2.14	4.43	4.84	0.17	0.18
	(4.27)	(5.38)	(0.97)	(1.00)	(3.14)	(3.39)	(0.16)	(0.18)
Observations	98	93	177	162	49	83	117	118

[1] Sowing week refers to the number of weeks deviated from the optimum sowing date identified with crop modelling (cf. Table 2).
[2] The category of rice variety is based on the duration of the growing season as follows. short = 95 days or less, medium-short = 96–120 days, medium-long = 121–140 days, and long = greater than 140 days.
[3] Ratio of rice income (%) denotes the share of 'a' rice income over annual farm income.

estimates associated with farmer's variety as the most used varieties are known to be available for farmers in the respective site and are likely to be used and representative of the variety used by a given farmer. In Myanmar, none of the varieties previously calibrated in ORYZA v3 were used by the surveyed farmers, thus the calibrated variety with the most similar crop growth duration in relation to the variety reported by farmers was used in the crop model simulations. The calibrated varieties used in the simulations were IR50 for short-duration varieties, IR38 for medium-duration varieties, and IR154 for long-duration varieties. Farmers reporting varieties with more than 130 days, that were not defined with photoperiod sensitivity, were classified as long-duration varieties. Similarly to previous studies (e.g., van Oort et al., 2011; Li et al., 2015), the calibration of a specific variety may increase uncertainties in Yp_c due to limited information from the farm survey on the characteristics of the variety and the inherent uncertainties in yield and crop phenology reported. Furthermore, most varieties recommended at the respective study sites were referred to by their growth duration class in addition to their name.

Over 95% of the surveyed farmers in Vietnam and Thailand used direct-seeding as their crop establishment method, whereas in Indonesia all farmers used transplanting. Thus, in the aforementioned sites, the dominant crop establishment method reported in the farm survey was used in the crop model simulations (Table 2). Conversely, 53% and 90% of the farmers in Myanmar used transplanting in the DS and WS, respectively, thus the crop establishment method reported by the farmers was used in the crop model simulations.

3.3. Stochastic frontier analysis and estimation of technical efficient yields (Y_{TEx})

Stochastic frontier analysis is a parametric method of frontier analysis that separates the effects of statistical noise and technical inefficiency in the production process (Aigner et al., 1977; Meeusen and Van Den Broeck, 1977). Stochastic frontier analysis was used to estimate the technical efficient yield (Y_{TEx}) and the efficiency yield gap (i.e., difference between Y_{TEx} and Ya). The approach considers the effects of biophysical control variables and production factors on crop yields while estimating two random errors, v_i and u_i. The former (v_i) captures random shocks and noise in the response variable (i.e., crop yield), whereas the latter (u_i) captures the contribution of sub-optimal crop management in relation to the time, space and form of the inputs used (Silva et al., 2017a, 2017b). The two random errors are thus important to isolate possible inaccuracies in the reported Ya from inefficient crop management practices. Y_{TEx} was estimated from a stochastic frontier model assuming a Cobb-Douglas functional form (i.e., considering first-order terms only) and accounting for inefficiency effects as follows:

$$lny_i = \alpha_0 + \sum_k^K \beta_k lnx_{ki} + v_i - u_i \quad (1)$$

$$v_i \sim i.i.d.N\left(0, \sigma_v^2\right) \quad (2)$$

$$u_i \sim i.i.d.N^+\left(\mu, \sigma_u^2\right), \mu = \sum_j^J \delta_j z_{ji} \quad (3)$$

$$Y_{TEx_i} = Ya_i \times exp\left(-u_i\right)^{-1} \quad (4)$$

Table 2
Input data and assumptions used in the ORYZA v3 crop model to simulate the three variants of the potential yield (Yp) defined in this study (cf. Fig. 1) for the farmer's fields surveyed across four lowland rice irrigated rice areas in Southeast Asia.

Input data	Description
Myanmar	
Farmer's sowing window DS	23-Nov-2011 to 11-Apr-2012
Farmer's sowing window WS	07-Jun-2011 to 20-Sep-2011
Optimum sowing date DS[1]	25-Jan-2012
Optimum sowing date WS[1]	14-Sep-2011
Crop establishment[2]	Transplanting and direct seeding
Varieties calibrated in Oryza[3]	Shwe Thwe Yin[5] (IR50; 105–110 days), Mestizo[5] (IR 138; 90–95 days), RC222[3] (IR154; 105–110 days) RC222[5] (IR 154; 105–110 days)
If not calibrated	<110 days = Local; >100 < 130 days = Mestizo; >130 days = RC222
Highest yielding variety	RC222
Vietnam	
Farmer's sowing window DS	22-Oct-2014 to 24-Dec-2014
Farmer's sowing window WS	05-Mar-2014 to 24-May-2014
Optimum sowing date DS[1]	26-Nov-2014
Optimum sowing date WS[1]	5-Mar-2014
Crop establishment	Direct seeding
Varieties calibrated in Oryza	Jasmine 85[6] (100–105 days), OM5451[6] (90–95 days)
If not calibrated	Jasmine 85 (most sown)
Highest yielding variety	Jasmine 85
Thailand	
Farmer's sowing window DS	24-Oct 2012 to 23-Jan-2013
Farmer's sowing window WS	15-May-2013 to 14-Aug-2013
Optimum sowing date DS[1]	20-Dec-2012
Optimum sowing date WS[1]	29-May-2013
Crop establishment	Direct seeding
Varieties calibrated in Oryza	RD31[6] (120–125 days)
If not calibrated	RD31
Highest yielding variety	RD31
Indonesia	
Farmer's sowing window DS	06-Mar-2013 to 14-Aug-2013
Farmer's sowing window WS	02-Oct-2013 to 25-Dec-2013
Optimum sowing date DS[1]	5-Jun-2013
Optimum sowing date WS[1]	18-Dec-2013
Crop establishment	Transplanting
Varieties calibrated in Oryza	Ciherang[6] (115–120 days), IR64[4] (95–100 days) and Inpari 6 (120–125 days)
If not calibrated	Ciherang (most sown)
Highest yielding variety	Inpari 6

[1] The optimum sowing date was estimated on a three-month window around the average actual sowing date, as the survey data showed a large range of sowing dates.

[2] In Myanmar the crop establishment method was set individually for each farmer.

[3] In Myanmar there was a wide range of varieties sown by the farmers, and none of them was calibrated in ORYZA v3, so the actual varieties were classified according to their duration. Yp for varieties with growth duration lower than 95 days was simulated using the variety IR38. Yp for varieties with medium duration ranging from 95 to 110 days was simulated using IR50. Yp for long duration varieties with more than 110 days was simulated using NSIC Rc222.

[4] Boling et al. (2010).

[5] Radanielson et al. (2019).

[6] Stuart et al. (2016).

where y_i is the actual yield (t ha^{-1}) of farmer *i*, and x_i is a vector of inputs and agronomic practices used by farmer *i*. The error term v_i is assumed to be independently and identically distributed (i.i.d.) following a normal distribution with mean 0 and variance σ_v^2. The error term u_i is also assumed to be i.i.d. but with a truncated-normal distribution with mean $\mu = \sum_j^J \delta_j z_{ji}$ and variance σ_u^2,where z_i represents a vector of agronomic and socioeconomic variables explaining the efficiency yield gap. β and δ are season-specific parameters to be estimated with maximum likelihood as described in Wang and Schmidt (2002). A log-likelihood ratio test was used to determine the appropriate specification between a Cobb-Douglas (Eq. (1)) and a specification for the production frontier including interactions between the continuous variables. The result of the log-likelihood ratio test indicated that a Cobb-Douglas functional form was more appropriate than the specification with interaction terms for both seasons in Myanmar and Indonesia (data not shown). Thus, the parameter estimates of the Cobb-Douglas functional form are presented in the main manuscript (Table 3) and the parameter estimates of the specification with interaction terms are presented in Suppl. Table S2. The parameters of the production function (Eq. (1)) and the inefficiency effects (Eq. (3)) were estimated simultaneously with the *sfcross()* function from the Stata package *sfcross* (Belotti et al., 2013) and with the dependent and independent variables log-transformed. Y_{TEx} was calculated based on the error term u_i following Eq. (4).

The stochastic frontier models were fitted for each site x season combination. The only exception was the DS data in Thailand for which the small sample size did not allow for reliable estimation of the production frontier. The vector of inputs x_i included six variables defined according to principles of production ecology (van Ittersum and Rabbinge, 1997). The variables referring to growth-defining factors included in the model were the sowing date (defined as the deviation expressed in number of weeks from the optimum sowing date identified with the crop model simulations) and type of rice variety grown (short-, medium-, and long-duration varieties, considering the latter as the reference category). The amounts of nitrogen (N), phosphorus (P) and potassium (K) applied were included in the model to capture the effects of growth-limiting factors on crop yields. Herbicide use (yes or no) was the only variable included in the model to capture the effects of growth-reducing factors on crop yields. Variables capturing the management of pests and diseases, or their incidence, in the surveyed fields, were not considered due to lack of data. The effects of climatic conditions on rice yields were assumed to be partly captured by the sowing date variable and no other control variables for variation in soil types were included in the analysis given the flat topography of the sites and the proximity of the fields surveyed (see Section 3.1).

The variability in the efficiency yield gap was explained using a second-stage regression in the production frontier (Eq. (3)). The drivers of the efficiency yield gap, z_i, included in the analysis were the number of fertilizer splits (#), the years of farming experience of the household head (# years), and the share of rice income in a given season to total annual income (%, see Section 3.4 for a definition of total annual income). It is hypothesized that efficiency yield gaps decrease with increases in farming experience and increases in the share of rice income to total annual income as such conditions may contribute to better crop management in terms of time, space, and form of the inputs applied. A positive sign on an estimated coefficient in the production frontier (Eq. (1)) indicates a productivity increasing factor, while a negative coefficient in the inefficiency estimation (Eq. (3)) indicates a reduction of the efficiency yield gap.

Table 3
Parameter estimates of the stochastic frontier models estimated for dry season (DS) and wet season (WS) rice across four lowland irrigated rice areas in Southeast Asia. The effect of interactions between variables are presented in Supplementary Table S2.

	Myanmar		Vietnam		Thailand	Indonesia	
	DS	WS	DS	WS	WS	DS	WS
Production frontier							
Nitrogen log	0.024	0.085***	0.089**	0.377***	−0.079	0.089***	0.107*
	(0.019)	(0.014)	(0.038)	(0.087)	(0.057)	(0.030)	(0.055)
Phosphorus log			−0.001	−0.172***	−0.016	0.011*	0.030
			(0.022)	(0.060)	(0.021)	(0.005)	(0.028)
Potassium log			0.010	0.069***	0.006		
			(0.014)	(0.023)	(0.009)		
Herbicide use	0.294***		−0.060*		0.254***		
	(0.056)		(0.036)		(0.066)		
Sowing week	0.000	−0.010	0.004	−0.006	−0.027***	0.020	−0.017
	(0.002)	(0.007)	(0.010)	(0.010)	(0.010)	(0.020)	(0.015)
Short duration			0.008	0.173***		−0.098	−0.098
			(0.027)	(0.044)		(0.196)	(0.080)
Medium-short duration	0.043	0.062			−0.047		
	(0.083)	(0.082)			(0.060)		
Medium-long duration	0.012	0.029					
	(0.077)	(0.054)					
Constant	7.654***	7.747***	8.558***	6.896***	9.035***	8.506***	8.157***
	(0.107)	(0.082)	(0.175)	(0.273)	(0.302)	(0.345)	(0.320)
Inefficiency term							
Fertilizer splits	−0.106	0.205	0.361	1.092	−65.752	0.089	0.030
	(0.069)	(0.223)	(0.903)	(0.784)	(186.922)	(0.091)	(0.145)
Farm experience log	0.053	0.360	−0.964	3.714***	−0.706	−0.054	0.072
	(0.110)	(0.394)	(2.181)	(0.815)	(15.132)	(0.078)	(0.113)
Ratio of rice income	0.045	−0.132	−0.021	−0.281	−0.607	−0.008**	−0.042***
	(0.045)	(0.095)	(0.051)	(0.534)	(1.811)	(0.003)	(0.016)
Constant	−4.207	−1.486	1.004	−2.847	2.204	1.035***	0.460
	(4.590)	(1.653)	(1.902)	(2.736)	(3.816)	(0.350)	(0.512)
Model performance							
TE score	0.929	0.912	0.947	0.707	0.821	0.495	0.692
$\sigma^2 = \sigma_u^2 + \sigma_v^2$	0.360***	0.588***	0.447***	0.781***	4.833***	0.516***	0.727***
$\lambda = \sigma_u^2/\sigma^2$	0.313***	0.626***	0.770***	0.810***	0.987***	0.999***	0.697***
Observations	98	92	177	162	83	83	115

Significance is indicated by the following codes: * $P < 0.10$, ** $P < 0.05$, and *** $P < 0.01$; Parenthesis show standard error of estimated coefficients. Skewed variables (i.e., mean < 0.05 or mean > 0.95 for binary variables), were not include in the analysis; Reference codes for variety types were as follows: Myanmar = long-duration, Vietnam = medium-short duration, Thailand = long-duration, Indonesia = medium-short duration.

3.4. Statistical analysis

Variability in farm size (ha) and share of rice income to total annual income (%) across sites was analyzed using boxplots. Total annual income is the sum of annual rice income and annual non-rice income, with the latter including income from a salary earner at private firms with regular pay, a salary earner at public facilities, a casual wage earner, wages from farm labor and, selling farm products other than rice. Rice yield response to N applied was assessed using quantile regression fitted to the 90th percentile of the pooled data with the *smf()* function of the *statsmodels* library in Python (Seabold and Perktold, 2010). A logistic functional form ($y = a + b \times x + c \times 0.99^x$) was assumed for this relationship, where y refers to actual yield (in t ha^{-1}) or yield gap closure (% of Yp_a) and x refers to the total amount of N applied with mineral fertilizers in each field.

4. Results

4.1. Bago, Ayeyarwady delta, Myanmar

During 2012 DS, Yp_a in Bago was on average 10.8 t ha^{-1}, Ya was 2.7 t ha^{-1} and the respective yield gap between Yp_a and Ya was 8.1 t ha^{-1} (Fig. 3A; Suppl. Table S1). The yield gap was mainly attributed to the resource yield gap (47% of Yp_a) and to the technology yield gap (25% of Yp_a; Fig. 3A). During the DS, the technology yield gap was mostly explained by the sowing date yield gap (20% of Yp_a, Fig. 3A). There was a large sowing window (November to April; Fig. 4A) in the DS resulting in a large variability of Yp_b with risk of high temperature, leading to yield loss associated with spikelet sterility (Suppl. Fig. 2). Indeed, rice crops sown between mid-December and mid-January had on average a 25% lower Yp_b than crops sown between late January and early February (Fig. 4A; Suppl. Fig. 2).

During 2012 WS, the Yp_a in Bago was on average 9.8 t ha^{-1}, Ya was 2.5 t ha^{-1} and the yield gap between Yp_a and Ya was 7.3 t ha^{-1} (Fig. 3B; Suppl. Table S1). The yield gap was mainly attributed to the resource yield gap (55% of Yp_a) and to the technology yield gap (16% of Yp_a; Fig. 3B). The sowing window during the WS was narrower than during the DS (between June and September), thereby lowering the contribution of the sowing date yield gap to 12% of Yp_a (Fig. 3B). The genetic yield gap was small in both seasons accounting for less than 8% of Yp_a (Fig. 3A and B). A total of 12 and 10 rice varieties were grown in the DS and WS, respectively, with the most used varieties, Manaw Thukka and Hmaw Be, sown by 41% and 35% of respondents, respectively (data not shown).

The major driver for rice yield variability in Bago was the use of herbicides in the DS and the amount of N applied in the WS (Table 3). During the DS, fields where herbicides were used yielded ca. 30% more than fields where no herbicides were used (Table 3). N applied had a statistically significant positive effect on rice yield in the WS only, but the effect was small. Indeed, no clear yield response to N applied was observed within the sample for Myanmar (Fig. 5). The small effect of N applied on rice yield in this site can be explained by the low N application rates observed in all surveyed fields, which ranged between nil and 50 kg N ha^{-1} in both seasons (Fig. 5), and possibly by other factors associated with poor crop management. This range of N application rate was the lowest observed across the four sites. Although there was no

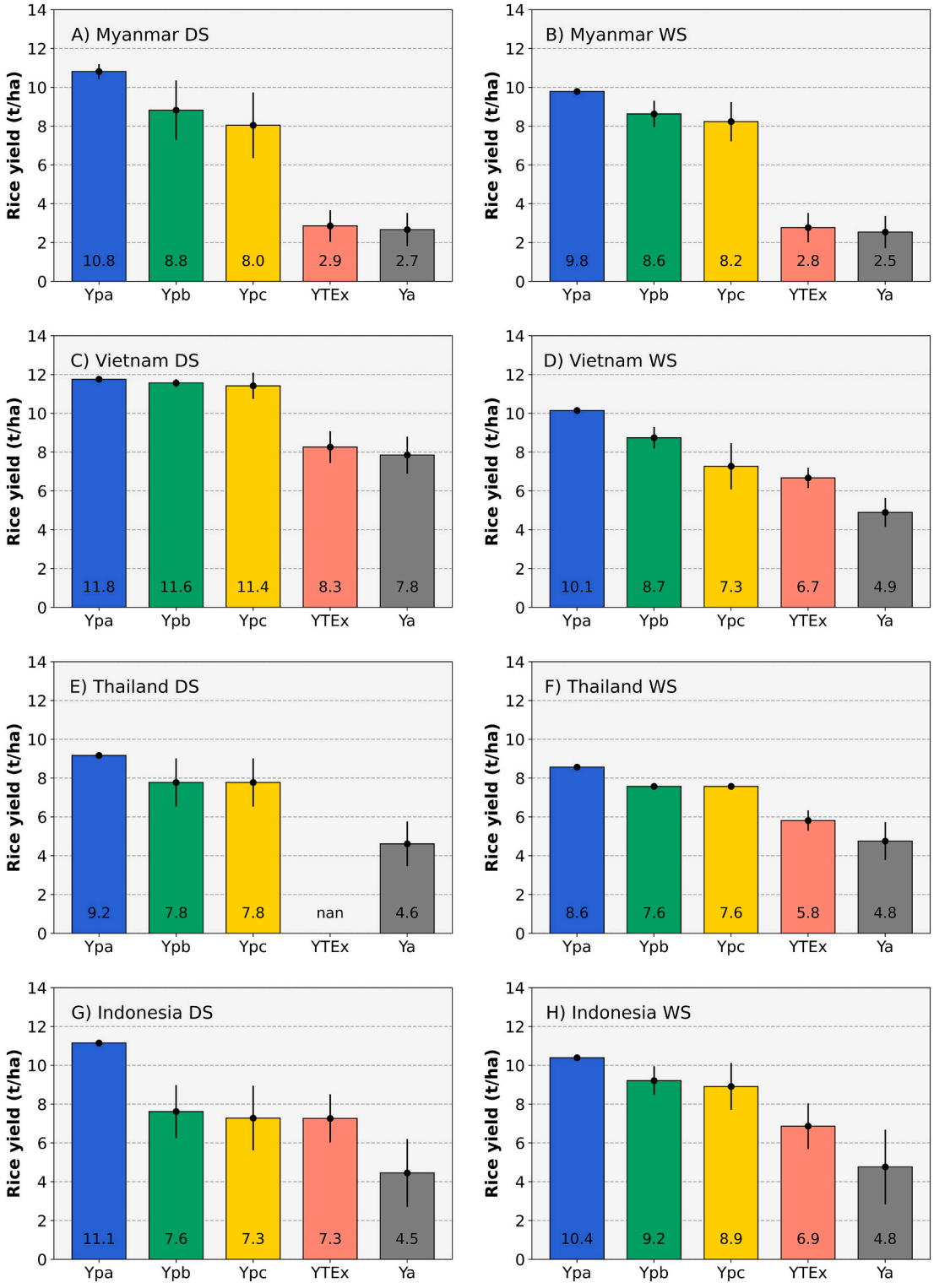

Fig. 3. Rice yields and yield gap decomposition into efficiency, resource, and technology yield gaps across four irrigated lowland rice areas in Southeast Asia. Values in each bar indicate the average across all fields analyzed in each site. Abbreviations are as defined in Fig. 1.

statistically significant effect of the proportion of rice income to total farm income on the efficiency yield gap (Table 3), increasing rice production in Bago is likely to improve farm profitability because ca. 80% of the total annual income was derived from rice farming alone and most households had access to at least ca. 2 ha of land (Fig. 6).

4.2. Can Tho, Mekong delta, Vietnam

During 2015 DS, the mean Yp_a in Can Tho was 11.8 t ha^{-1}, Ya was 7.8 t ha^{-1} and the respective yield gap between Yp_a and Ya was 4.0 t ha^{-1} (Fig. 3C; Suppl. Table S1). The yield gap was mostly explained by the resource yield gap, which accounted for 26% of Yp_a, while the efficiency and technology yield gaps were small, 4% and 3% of Yp_a,

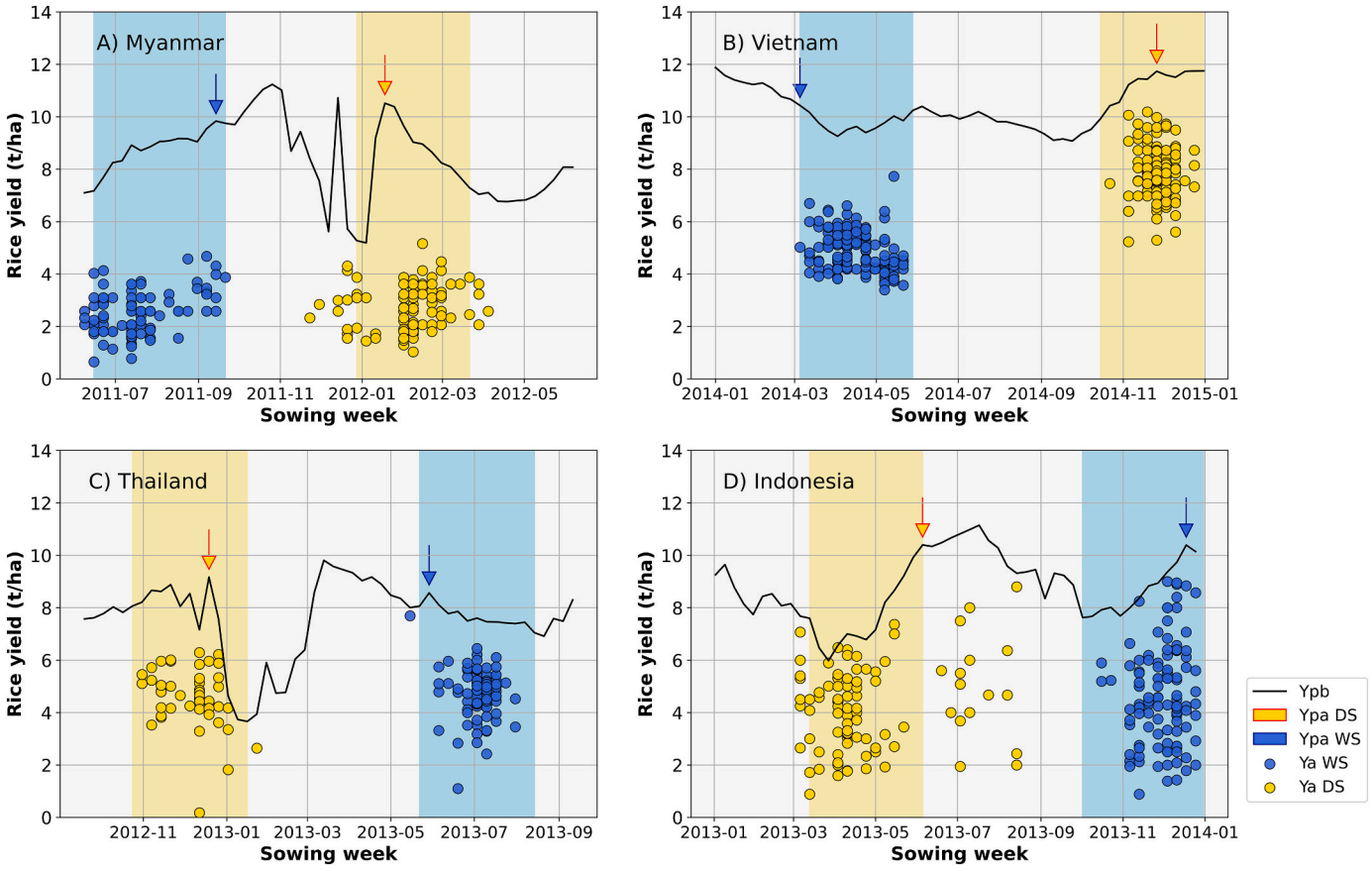

Fig. 4. Distribution of farmers' actual yields (Ya) in comparison with the simulated potential yield (Yp) across different sowing dates in four irrigated lowland rice areas in Southeast Asia. The simulated Yp for optimum sowing date and the highest yielding variety (Yp_a) is indicated by the arrows. The simulated potential yield for farmers' sowing dates and highest yielding variety (Yp_b) is indicated by the solid line. Yp_b was modelled using the rice varieties presented in Table 1. Codes: DS = dry season, WS = wet season.

respectively (Fig. 3C). Differences between Yp_a, Yp_b, and Yp_c during the DS were negligible (Fig. 3C). The small sowing date and genetic yield gaps in the DS are the result of a relatively stable Yp_b between October 10 and December 17 (Fig. 4B), and to the fact that 82% of farmers used the same variety, c.v. Jasmine 85 (data not shown).

During the 2015 WS, the mean Yp_a in Can Tho was 10.1 t ha^{-1}, Ya was 4.9 t ha^{-1} and the yield gap between Yp_a and Ya was 5.2 t ha^{-1} (Fig. 3D; Suppl. Table S1). The yield gap was mostly explained by the technology and efficiency yield gaps, which were 27% and 18% of Yp_a, respectively, while the resource yield gap was 6% of Yp_a (Fig. 3D). The technology yield gap in the WS was equally explained by the sowing date and the genetic yield gaps, which accounted for 15% of Yp_a each (Fig. 3D). The relatively large technology yield gap in the WS was the result of a sowing window spanning over 3 months, between March and May (Fig. 4B), and of eight rice varieties being used, with the most used variety, OM 5451, being sown by 61% of the surveyed farmers (data not shown).

N applied was the main driver of rice yield in Can Tho in both seasons, but there was also a positive effect of K applied on rice yield during the WS (Table 3). For instance, increasing N by 1% increased rice yield by 0.09 and 0.38% in the DS and WS, respectively (Table 3). N application rates ranged between 30 and 150 kg N ha^{-1} in the WS and between 70 and 150 kg N ha^{-1} in the DS (Fig. 5). This range of N application rates corresponded to the steep slope of the curve characterizing the yield response to N applied for the pooled data across the four sites (Fig. 5). There was also a negative effect of P applied on rice yield in the WS and rice yield was 17% greater for short-duration varieties than for long-duration varieties. None of the factors considered in the analysis had a significant effect on the efficiency yield gap during the DS, whereas farmers reporting a greater number of years of farming experience exhibited greater efficiency yield gaps during the WS (Table 3). Farmers in Can Tho managed farms with an average of 2 ha and no larger than 5 ha (Fig. 6A) and rice income accounted for ca. 50% of the total annual income for about half of the farmers surveyed (Fig. 6B).

4.3. Nakhon Sawan, Central Thailand

Yp_a during the 2013 DS in Nakhon Sawan was on average 9.2 t ha^{-1} and Ya was on average 4.6 t ha^{-1}, which translated in a yield gap of 4.6 t ha^{-1} (Fig. 3E; Suppl. Table S1). The small sample size during the DS did not allow to disentangle efficiency and resource yield gaps, yet the yield gap between Yp_c and Ya accounted for 35% of Yp_a and the technology yield gap accounted for 15% of Yp_a (Fig. 3E). There was a wide sowing window during the DS spanning between November and January, with considerable decreases in Yp_b after December (Fig. 4C). High temperatures, leading to heat stress, occurred during March and negatively affected the Yp_b of rice crops sown between January and February (Suppl. Figs. S1 and S3).

During the 2013 WS, Yp_a and Ya in Nakhon Sawan had an average value of 8.6 and 4.8 t ha^{-1} respectively, corresponding to a yield gap of 3.8 t ha^{-1} (Fig. 3F; Suppl. Table S1). The yield gap during the WS explained by the efficiency, resource, and technology yield gaps accounted for 12, 21, and 12% of Yp_a, respectively (Fig. 3F). The length of the sowing window in the WS was comparable to the DS, yet there was much less variation in Yp_b during the WS than in the DS (Fig. 4C). It was

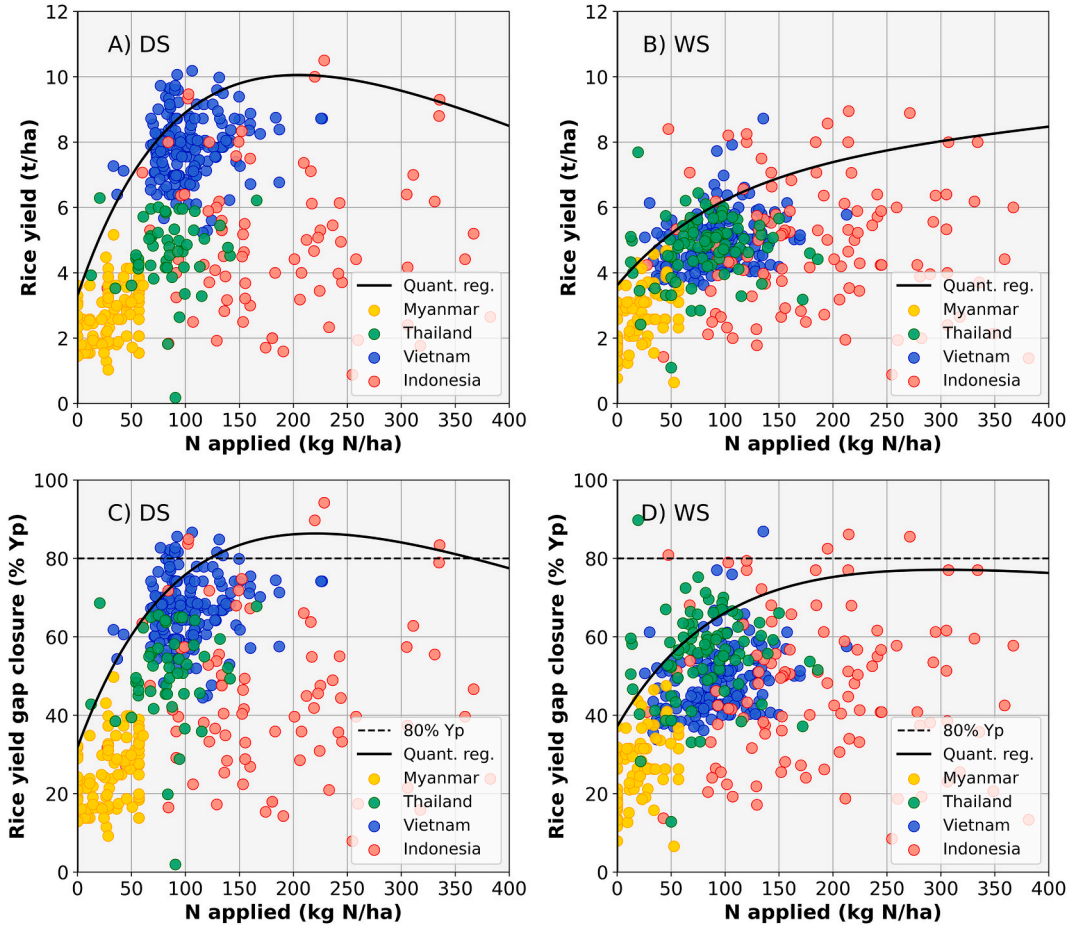

Fig. 5. Rice yield response to N applied across four irrigated lowland rice areas in Southeast Asia. Panels (A) and (B) present rice yields in absolute terms during the dry season (DS) and wet season (WS), respectively. Panels (C) and (D) present rice yield gap closure with actual yields shown as a proportion of the simulated potential yield (Yp_a) during the DS and WS, respectively. Each observation corresponds to one individual field in each of the four irrigated lowland rice areas. The solid line depicts a quantile regression fitted to the 90th percentile of the pooled data and the dashed line in Panels (C) and (D) shows a relative yield gap closure of 80% of Yp_a.

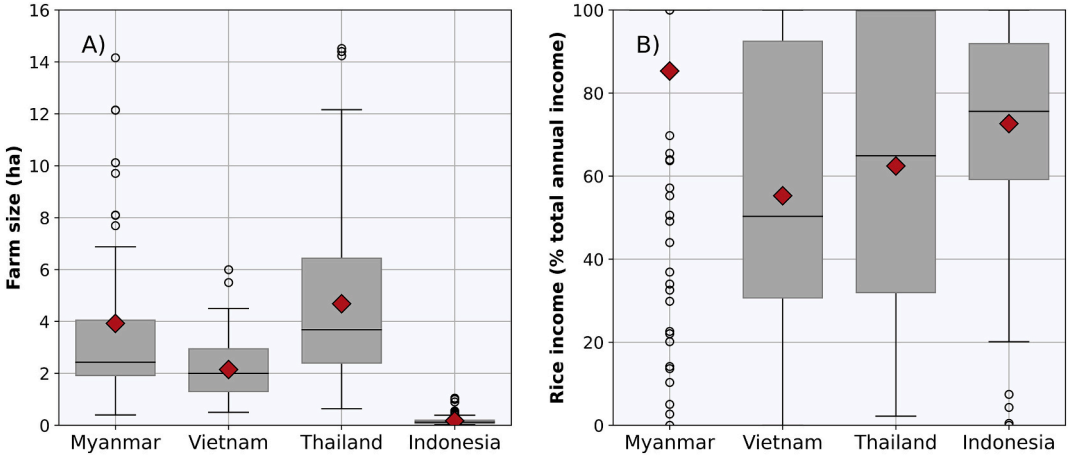

Fig. 6. Boxplots of farm size in ha (A) and share of rice income in total annual income in % (B) in four irrigated lowland rice areas in Southeast Asia. Data are pooled for the wet and dry seasons in each site. Red diamonds indicate the mean. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

not possible to decompose the technology yield gap further for this site as only one rice variety was calibrated in ORYZA v3 (cf. Table 1). Yet, all varieties used by farmers had a growth duration of 110–120 days (data not shown).

The drivers of rice yield variability in Nakhon Sawan were the use of herbicides and the difference in sowing date relative to the optimum sowing date identified with crop modelling (Table 3). Similarly to Bago, fields where herbicides were used yielded 25% more than fields where

no herbicides were used but the latter accounted only to ca. 5% of the sampled fields (cf. Table 1). Moreover, one week deviation from the optimal sowing date resulted in a 10% decrease in rice yield. There was no statistically significant effect of N applied on rice yield in Nakhon Sawan, which confirms the visual observations presented in Fig. 5 for this site. Similarly to Can Tho, N application rates in the WS and in the DS ranged between 40 and 150 kg N ha^{-1}, which can be considered optimal for most fields (Fig. 5). None of the inefficiency effects considered in the stochastic frontier analysis were identified as determinants of the efficiency yield gap in this site (Table 3). Farmers in Nakhon Sawan had larger farm sizes than farmers at the other sites (Fig. 6A), with an average farm size of ca. 5 ha and about half of the farmers surveyed reporting farm sizes above 4 ha. Similar to Can Tho, rice income accounted for ca. 60% of the total annual income (Fig. 6B).

4.4. Yogyakarta, Java, Indonesia

During 2014 DS, Yp_a in Yogyakarta was on average 11.1 t ha^{-1}, Ya was 4.5 t ha^{-1} and the respective yield gap between Yp_a and Ya was 6.6 t ha^{-1} (Fig. 3G; Suppl. Table S1). Most of the yield gap in the DS was attributed to the technology yield gap (34% of Yp_a) and to the efficiency yield gap (25% of Yp_a; Fig. 3G). The technology yield gap was mostly attributed to the sowing date yield gap in the DS with the genetic yield gap contributing to less than 5% of Yp_a (Fig. 3G). Rice was sown across a five-month period during the DS (between March and August; Fig. 4D), with the sowing date yield gap representing 32% of Yp_a (Fig. 3G). Farmers who planted between June and August were likely to be those with irrigation available all year, who either planted late or planted a second DS rice crop that was not differentiated in this analysis from the early DS crop, as this was not clarified during the farm survey.

In the 2014 WS, slightly smaller yields and yield gaps were observed in Yogyakarta than in the DS: Yp_a and Ya were on average 10.4 and 4.8 t ha^{-1}, respectively, corresponding to a yield gap of 5.6 t ha^{-1} (Fig. 3H; Suppl. Table S1). The yield gap was mostly explained by the resource yield gap (19% of Yp_a) and by the efficiency yield gap (11% of Yp_a; Fig. 23H). The technology yield gap in the WS was also mostly attributed to the sowing date yield gap (Fig. 2H). During the WS, rice was sown between October and January (Fig. 4D) and the sowing date yield gap explained about 10% of Yp_a (Fig. 3H).

N applied had a significant positive effect on rice yield, with a 1% increase in N applied resulting in ca. 0.10% increase in rice yield during both seasons, respectively (Table 3). There was also a positive effect of P applied on rice yield during the DS (Table 3). Across the four sites, N application rates were greatest in Yogyakarta, ranging between 75 and 350 kg N ha^{-1} (Fig. 5). N application rates beyond 180–200 kg N ha^{-1} translated into marginal, or even negative, rice yield response to N applied when considering the pooled data (Fig. 5). Such negative yield response to N applied were not captured in the stochastic frontier analysis (Table 3) most likely because squared terms and interactions between variables were not considered in the fitted models. The efficiency yield gap decreased with increasing share of rice income to total annual income (Table 3), meaning that inputs applied were better managed in farms relying more on rice as a source of income. Indeed, rice income accounted for ca. 70% of the total annual income in Yogyakarta (Fig. 6B), despite the extremely small farm sizes at this site (Fig. 6A).

5. Discussion

5.1. Drivers of rice yield gaps in Southeast Asia

Crop modelling was combined with the analysis of farm survey data to estimate and decompose rice yield gaps across four sites in Southeast Asia (Fig. 2). The rice yield gap was largest in Bago (75% of Yp_a), followed by Yogyakarta (57% of Yp_a), Nakhon Sawan (47% of Yp_a) and Can Tho (44% of Yp_a; Figs. 2 and 5). Building upon the study by Stuart et al. (2016), these results refer to both wet and dry season rice crops and consider field-specific yield potentials, reflecting the highest yielding varieties available to farmers and the optimal sowing dates within the range of sowing dates reported by farmers.

Most of the yield gap for rice in Bago, Myanmar, was attributed to the resource yield gap, followed by the technology (sowing date) yield gap (Fig. 3A and B). Increasing input use, namely fertilizers, and proper weed control is thus necessary if yield gaps are to be narrowed in Bago (Figs. 3A, B and 5; Thwe et al., 2019; Radanielson et al., 2019). N application rates in Bago were well below 60 kg N ha^{-1} in most fields, confirming the low amounts of inputs used and the low level of yield gap closure in this site (Fig. 5). Despite the small amount of N applied, other factors (e.g., pests, diseases and weeds, balanced fertilization, or timing of N application) may also be reducing or limiting rice yield. Improvements in pest, disease, and nutrient management are likely to be needed, in tandem with increases in N applied, for intensifying rice production in this site. The levels of fertilizer use and rice yield observed in Bago are comparable to those observed in the 1970s for rice crops in Central Luzon, the Philippines (Kajisa and Payongayong, 2011; Laborte et al., 2012). Moreover, narrowing the sowing date yield gap through early sowing in the DS or late sowing in the WS within the three-month sowing window also offers opportunities to increase rice yield (Fig. 4A). The sowing date yield gap estimated in Bago also indicates high climatic risk for rice cropping in the region within the sowing window reported by the farmers.

Rice yield gaps in Yogyakarta, Indonesia, were mostly attributed to efficiency and technology (sowing date) yield gaps (Fig. 3G and H). Resource yield gaps were negligible in this site during the DS, where indeed excessive N application rates were observed in both DS and WS (Fig. 5). Such large N application rates are a typical feature of high-yielding cropping systems (Nayak et al., 2022; Cui et al., 2018; Silva et al., 2017a, 2017b). The fairly large resource yield gap observed in the WS was surprising given the excessive N rates observed in farmers' fields (Fig. 5), most likely due to limitations in the stochastic frontier analysis (see Section 5.3). Yet, farmers reported yield losses due to blast and bacterial leaf light during this WS, possibly due to excessive use of N, which might explain why Y_{TEx} was smaller than Yp_c (Figs. 3H). Thus, further increases in rice yield in this site must be derived through a combination of reductions in applied N (Fig. 5) and increases in resource-use efficiency via better timing, space, and form of the inputs applied (Fig. 3G and H), and adaptive seasonal management such as shifting of sowing dates (Fig. 4D). The sowing window in the DS was wide (Fig. 4D) as farmers were sowing following the irrigation schedule established by the national irrigation authority. Optimization of sowing dates in the DS is only feasible then if the irrigation water scheduling can be adapted accordingly. Late DS sowing and early WS sowing also presented a risk of heavy rainfall at harvest which has a significant effect in securing timely harvesting and grain quality. Future studies accounting for the impact of climatic risk on harvest time and grain quality are needed to formulate adapted recommendations contributing to reduce the sowing date yield gap in Yogyakarta. Moreover, intensification using three crops per year in Yogyakarta is limited by water availability during the latter half of the dry season.

The efficiency, resource, and technology (sowing date) yield gap contributed equally to the rice yield gap in Nakhon Sawan, Thailand, during the WS (Fig. 3F). The relative contribution of the intermediate yield gaps is comparable to that observed for rice farming in Central Luzon, Philippines (Silva et al., 2017a, 2017b), as too the level of yield gap closure (ca. 50% of Yp_a). Efficiency and resource yield gaps had a similar magnitude in Nakhon Sawan (Fig. 3E and F), and herbicide use was an important factor associated with narrowing the resource yield gap (Table 3). Earlier sowing is also likely to increase rice yields, particularly during the DS (Fig. 4C). Indeed, long-term analysis of rice yield response to temperature indicated that late sowing of DS rice during the months of January–March resulted in greater risks of spikelet sterility due to temperature stress (Suppl. Fig. S3). Increasing rice

productivity in the DS, the high yielding season of the year, thus requires adaptive management to climate variability such as the use of varieties with adapted growth duration and improved high temperature stress tolerance.

In Can Tho, Vietnam, yield gaps for DS rice were mostly attributed to the resource yield gap while for WS rice both efficiency and technology yield gaps contributed similarly to the total yield gap (Fig. 3C and D). Yet, it is questionable whether yield gaps should be narrowed further in this site as yield gap closure for most fields in the DS and for some fields in the WS was close to 80% of Yp_a (Fig. 5), which is often cited as the attainable yield target. Yield gap closure beyond 80% substantially reduces economic gains and increases risk of pests, disease, and lodging (van Ittersum et al., 2013; Stuart et al., 2016). Indeed, the sowing date yield gap was small in Can Tho despite the wide sowing window observed in the DS and WS. Yp_b presented a steady trend within each cropping season with almost few or no fluctuations compared to the other sites (Fig. 4B). This lower Yp_b variability indicates that sowing date was not a key factor driving rice productivity particularly in the DS. Furthermore, the resource yield gap for DS rice crops in Can Tho reported here may be overestimated, and consequently the efficiency yield gap underestimated, due to the small sample size available to estimate Y_{TEx}, hence results need to be interpreted with caution. Current N application rates are likely to be nearly optimal for this site (Pampolino et al., 2007), but a few fields appear to have excessive N rates above 150 kg N ha^{-1} (Fig. 5). Results of on-farm trials in Can Tho during the DS showed low yield gain from the application of best management practices (Stuart et al., 2018a), and seasonal increases in rice yield by farmers practicing site-specific nutrient management in Southern Vietnam were also reported to be only 0.2 t ha^{-1} (Pampolino et al., 2007). During the WS, there is scope to increase rice yield through the combined adoption of high yielding varieties, timely sowing, and improved crop management in relation to the time, space and form of the inputs applied (Fig. 3D). Yet, highest-yielding fields during the WS already applied recommended N rates (Stuart et al., 2016). This confirms the findings of Huan et al. (2008) who also recommended limited and efficient use of N fertilizers in the Mekong delta as a means to reduce yield losses from pests and diseases during the WS.

5.2. Scope for sustainable intensification and policy recommendations

Rice production systems in Southeast Asia exhibit different stages of intensification, hence the scope to prioritize 'sustainability' and 'intensification' is site-specific (Silva et al., 2021; Struik and Kuyper, 2017; Stuart et al., 2016). Based on the level of yield gap closure and N application rate during the survey periods, intensification of rice production in Bago through increases in fertilizer use should be prioritized (Stuart et al., 2016; Thwe et al., 2019), whereas in Nakhon Sawan and Can Tho further increases in rice yield must be accompanied by increases in nutrient-use efficiency (Dobermann et al., 2002; Witt et al., 1999; Cassman et al., 1996) and in Yogyakarta by reductions in fertilizer use, particularly of N fertilizers (Fig. 5).

Socio-economic considerations are also important to delineate the scope for sustainable intensification at local level (Takahashi and Otsuka, 2009; Silva et al., 2018; Flor et al., 2021). For instance, intensive use of fertilizers (Fig. 5), low levels of mechanization (Agus et al., 2019), and the preference for transplanting as a crop establishment method (Table 1) may be related to the small farm sizes observed in Yogyakarta (Fig. 6A). Conversely, the relatively large farm sizes might have triggered the adoption of direct-seeding as a crop establishment method and allowed for the mechanization and intensive rice cultivation in Can Tho (Stuart et al., 2018a) and Nakhon Sawan (Stuart et al., 2018b). Small farm sizes were essential for the Green Revolution in Asia (Larson et al., 2016), yet they also hinder economies of scale. The 'Small Farms, Large Fields' (SFLF) model developed in Vietnam is a possible solution to support smallholders within large production areas by creating favorable conditions for the coordinated application of improved technologies and standardized practices for economies of scale and stabilizing output markets (Thang et al., 2017; Flor et al., 2021). The model is recognized as a solution to the constraints faced by smallholders for mechanization and it offers them a bargaining power in both input and output markets (Mohanty et al., 2017, 2018).

The share of annual income derived from rice farming also helps contextualize the contribution of rice to the economic performance of small-scale rice farms. Narrowing yield gaps in Bago and Yogyakarta will most likely translate into income increases for farmers under current conditions as ca. 80% of total annual income in these sites was derived from rice alone (Fig. 6B). The results also indicate that farms with a greater share of rice income in Yogyakarta have smaller efficiency yield gaps (Table 3), implying these farms prioritize crop management for rice in terms of the time, space, and form of inputs applied better than farms with a smaller share of rice income. Further research is required to better understand the linkages between income from rice and rice crop management, also considering off-farm income and job opportunities beyond farming.

5.3. Limitations and future research

Crop modelling is useful to define upper ceilings and benchmarks for actual yields in farmers' fields and to disentangle sowing date yield gaps from genetic yield gaps (Fig. 2). Yet, the approach followed here entails limitations that require attention in future studies. First, the varieties reported by farmers were mostly characterized by growth duration which makes it hard to capture the full variability in yield potential between the different varieties. As a result, estimates of yield potential incur uncertainties and the contribution of the genetic yield gap to the technology yield gap might be underestimated in this study (Fig. 3). Second, variety by sowing date interactions were not explored and hence, it remains unclear whether some varieties perform better when sown in different periods of the wide sowing windows observed in most sites (Fig. 4). Third, optimal sowing dates were identified at crop level based on a single growing season rather than at cropping systems level based on long-term weather patterns and risks associated with water and temperature stresses. For instance, the optimum sowing date of the DS in Bago was observed to be mid-February when considering historical weather data (Radanielson et al., 2019), whilst within the cropping season surveyed in this study, the optimum sowing date was at the end of January, a period with higher risk of temperature stress (Suppl. Fig. 2). Recommendations for shifting sowing dates are thus season dependent. The optimum sowing dates identified are for maximum yield in a given season and would still allow the establishment of the concurrent crop of the year (Fig. 4). Optimizing sowing dates for the two or three crops a year to maximize annual rice production would most likely result in different optimum sowing dates, a topic that merits future research.

The stochastic frontier analysis presented here has a number of limitations. First, the effects of pests and diseases could not be considered due to lack of data meaning that efficiency yield gaps may be overestimated in sites or seasons affected by these factors. This is particularly important in the analysis for Indonesia where positive effects of N on rice yield were identified (Table 3), despite the negative or small yield response to N applied identified visually (Fig. 5). The latter might be the result of lodging or pressure from pests and diseases (i.e., neck blast and bacterial leaf blight) at high N application levels. Second, socio-economic proxies associated with the efficiency yield gap were included in the analysis and future studies should better understand the effects of time, space, and form of inputs on the efficiency yield gap. Third, the lack of consideration of squared terms in the stochastic frontier models means that non-linear effects could not be accounted in the analysis. Second-order terms would be needed to capture a potential negative yield response to N applied in Indonesia, as identified in the quantile regressions fitted to the pooled data (Fig. 5). Interactions between the variables included in the production frontier were tested

(Supplementary Table S2) but yielded inconclusive results possibly due to the small sample size. Finally, the farmer field data used in this study were collected between 2012 and 2015 and it is possible that since then several innovations and technological changes could have occurred in the sites studied. Analysis of more recent and independent data are needed to validate the findings presented here.

Overcoming some of the limitations described requires long-term assessments at cropping systems level (Guilpart et al., 2017; Silva et al., 2017a, 2017b). The sequence of crops within the cropping system determines the sowing and harvest dates for each single crop and the overall performance of the cropping sequence depends on the performance of each individual crop. The farm survey failed to differentiate between the early DS and the second late DS rice crop in Yogyakarta, which biases the optimum sowing date estimated for the DS in this site (Fig. 4D). Future studies also need to pay more attention to the role of reducing factors, particularly pests and diseases, on rice yield (e.g., Buresh et al., 2021). Finally, it is important to broaden the yield gap analysis presented here with a sustainability assessment considering profitability, resource-use efficiency, and greenhouse gas emissions as well as synergies and tradeoffs between the different indicators (Devkota et al., 2019; Silva et al., 2018).

6. Conclusion

Rice yield gaps across four sites in Southeast Asia were decomposed into efficiency, resource, and technology yield gaps using a combination of stochastic frontier analysis and crop growth modelling applied to farm survey data. Yield gaps were greatest in Bago, Myanmar (75% of Yp), and mostly attributed to resource and technology yield gaps. Yield gaps were intermediate in Yogyakarta, Indonesia (54% of Yp) and in Nakhon Sawan, Thailand (47% of Yp). In Yogyakarta, yield gaps were mostly attributed to efficiency and technology yield gaps whereas in Nakhon Sawan yield gaps were equally attributed to the three intermediate yield gaps. Yield gaps were smallest in Can Tho, Vietnam (44% of Yp) and mostly attributed to the technology yield gap in both seasons. The efficiency yield gap was also important to explain rice yield gaps in Can Tho during the WS, and the same is likely to be true in the DS as the small sample size might lead to overestimation of the resource yield gap (and hence, underestimation of the efficiency yield gap) estimated here. The current level of yield gap closure and N application rates indicate there is a large scope to increase rice production in Bago (Myanmar) through increases in fertilizer inputs, whereas in Yogyakarta (Indonesia), Nakhon Sawan (Thailand) and Can Tho (Vietnam) increases in rice production must be accompanied by increases in nutrient-use efficiency. Increasing nutrient-use efficiency in Nakhon Sawan (Thailand) and Can Tho (Vietnam) requires fine-tuning fertilizer management in relation to the timing, space, and/or form of the inputs applied. Conversely, increasing nutrient-use efficiency in Yogyakarta (Indonesia) requires reductions in the amounts of N applied in addition to fine-tuning fertilizer management practices. Separating efficiency and resource yield gaps helped identifying sites where site-specific nutrient management technologies should be targeted and where fine-tuning fertilizer application rates can contribute to increase nutrient-use efficiency, respectively. Future studies should investigate the role of yield-reducing factors, particularly pests and diseases, on rice yield gaps and to broaden the assessment presented here to other economic and environmental indicators, including the synergies and tradeoffs between them at crop and at cropping system levels. A better understanding of socio-economic factors affecting sowing dates is also needed, such as timely access to irrigation water, machinery, and labor. In conclusion, the major rice areas in Southeast Asia exhibit different stages of agricultural intensification that require different approaches to ensure sustainable rice production in the future. By breaking down the yield gap into different components, context-specific opportunities to narrow yield gaps were identified, providing valuable insight to target sustainable intensification of rice production in the region.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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